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# An efficientArtifact Free Denoising Technique for MR Images relying onTotal Variation Thresholding in Wavelet Domain

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## Abstract
The process of removing different noises in magnetic resonance images is an important and challenging issue in clinical practices for the diagnosis using medical imaging. Various medical image restoration techniques using denoising algorithms with the help of wavelet transform are emerging out to a very abundant range in recent years. It has been apparent that different methods were deployed to perform a threshold operation on the wavelet coefficient of noise corrupted medical image, which restore the precise image as the original one. However, the primary demerit of wavelet denoising is pseudo-Gibb's phenomenon, while reconstructing the smoothened medical image. The Total Variation method is very useful for the recovery of blocky, possibly discontinuous images, from a noisy background. Our approach optimized the threshold value of the wavelet decomposed image by TV minimization and then denoised by soft or hard thresholding. The TV method eliminates Gibb's phenomena and thus restores sharp discontinuities. In this algorithm, we perform the TV minimization technique on the wavelet threshold coefficient before thresholding. The proposed method increases the SNR by more than 32 dB without distorting the image, whereas standard wavelet denoising methods improve the SNR by less than 20 dB and with some distortion. In addition, its computation time is more than six times faster.

***Keywords:*** *Wavelets, Total Variation, Denoising, Magnetic Resonance Images, Medical Images.*

**Nomenclature**

| | |
|---|---|
| SNR | Signal to Noise Ratio |
| TV | Total Variation |
| CT | Computed Tomography |
| MR | Magnetic Resonance |
| PSNR | Peak Signal to Noise Ratio |
| RMSE | Root Mean Square Error |
| SD | Standard Deviation |
| DWT | Discrete Wavelet Transform |
| LL | Low - Low |
| LH | Low - High |
| HL | High - Low |
| HH | High - High |

## 1. Introduction
The current advancements in computerized imaging technology, for example, CT and MR have altered the present day clinical practices for diagnosis. Nowadays most of the patients are interested in avoiding intrusive and often a hazardous process to identify their different types of illness. The extensive utilization of digital imaging in clinical diagnosis, the necessity of a precise nature of medical images turns into a significant issue. The sharp, bright and noise free medical images can achieve the best possible diagnosis. The advancements in image acquisition techniques bring images with high spatial and intensity resolution. At the same time noise plays a predominant role on deteriorating the quality of the medical image. So the effect of noise remains the transcendent issue in breaking down the quality. Reducing distortion due to the noises in these medical images stays one of the significant difficulties in the investigation of medicinal imaging. Therapeutic medical images, from different medical imaging modalities such as x-ray, computed tomography, magnetic resonance, positron emission tomography, and single positron emission computed tomography, have detailed and miniature information about human organs. These images are distorted during capturing and transmission, which leads to the wrong diagnosis in medicinal practices [1].

In recent years, various medical image restoration techniques using denoising algorithms with the help of wavelet transform are emerging out to a very abundant range. In these algorithms noise removal are performed by thresholding the noisy wavelet coefficients. The primary difficulty of these algorithm is the effect of Gibb's phenomena, which produces some distortion in denoised image. The TV method eliminates Gibb's phenomena and thus restores sharp discontinuities. In this algorithm, we perform the TV minimization technique on the wavelet threshold coefficient before thresholding. The proposed method increases the SNR by more than 32 dB without distorting the image, whereas standard wavelet denoising methods improve the SNR by less than 20

dB and with some distortion. In addition, its computation time is more than six times faster.

The primary objective of image renovation using denoising techniques is to reconstruct the original image from a noise corrupted image [2],

$$g(m,n) = f(m,n) + \eta(m,n) \quad (1)$$

In this image degradation model the degraded image g (m, n) is resulted by additive process among the original image f (m, n) and the noise component η (m, n), at a pixel (m, n). This best straightforward image degradation model exhibits the impact of noise on medical images with the inclusion of zero mean with variance σ2 Gaussian white noise. A few strategies based on linear denoising model using the averaging technique to eliminate the noise with the reconstruction of the original image 'f,' which can be implemented by the Gaussian smoothing model [3], the TV minimization [4] , and wavelet thresholding techniques [5]. The drawback of the above averaging techniques based on linear denoising model is the failure of preserving the edges efficiently, due to the discontinuity nature of the edges in an image. The preservation of images during the entire denoising process is accomplished by the nonlinear denoising with TV based filtering method, presented by Rudin, Osher, and Fatemi. Even though this technique provides a great way to safeguard edges, but modifies the smoothly changing regions in the original image into piecewise constant regions in the resultant images.

The latest wavelet thresholding based denoising techniques demonstrated promising since they are fit for eliminating the noise while keeping up the high-frequency pixels of interest. Since the start of the wavelet in image processing, it has been seen that wavelet thresholding [6] is considerable enthusiasm for expelling noise from signals and images. The strategy comprises to divide the noisy information into an orthogonal wavelet basis, to stifle the wavelet coefficients littler than a given magnitude by utilizing soft or hard thresholding, and to change the information over into the original space. Be that as it may, the wavelet thresholding strategy is as yet a regularization process and the present estimator oscillation in the region of a pixel's discontinuities. Such oscillations are very similar to the Gibbs phenomenon revealed by Fourier thresholding. They are called pseudo-Gibbs phenomena.

In practice, to approximate an original image from the noisy environment, the most as often as possible utilized techniques depend on the minimum squares criteria [7]. The method of reasoning originates from the statistical arguments that the minimum square estimation is the best over a whole gathering of every single conceivable image. This process is depending on the L2 norm. Conversely, it has been inferred that the correct norm for images is the TV norm and not the L2 norm. TV norms are principally Lj norms of derivatives, and hence La approximation techniques are more suitable for the substance of image restoration. The strategy we are presenting in this paper by combining the merits of both wavelet and TV method which reduce the artifact with the elimination of Gibbs phenomena effect.

The remaining content of this research paper is given in five sections. Section 2 provides the literature of wavelet denoising methods, section 3 explained the TV minimization technique, section 4 explained the proposed denoising technique with the evaluation parameters for analysing the denoised images, section 5 gives the experimental results with analysis, and finally, section 6 concludes our denoising technique.

## 2. Wavelet Denoising

The filtering in both spatial and transform domain [8] are the two fundamental ways to restore medical images. A conventional approach is to apply the spatial filter to eliminate noise from the corrupted image, which is suitable for the smooth signal. The wavelet-based denoising technique was presented [9], to conquer the shortcoming of the spatial filtering. The properties sparsity and multiresolution structure of wavelets give a better performance in image denoising.

Wavelet transform denoising technique comprises three major stages. [10].

1. Determine the LL, LH, HL, and HH wavelet coefficients of the degraded image;
2. Enhance the wavelet coefficients of degraded image using suitable technique;
3. Perform the inverse transform on the improved coefficients;

Soft and Hard thresholding is the suitable techniques to enhance the coefficients belongs to HH band. In thresholding coefficients which are higher than T, are subtracted from the threshold value T and replaced with the resultant value, and other coefficients are merely replaced by zero. The exact selection of the threshold value is a challenging task to get good performance, in this method of denoising. For better performance, some researchers have considered wavelet shrinkage, [11], in which the enhanced wavelet transformed coefficients are estimated using maximum a posteriori probability estimator [12].

In medical imaging diagnosis, the noise components occupy in high frequency bands and the low frequency components are dominated by the signal. Wavelets can take into consideration the joint resolution in both the spatial and frequency domain. Wavelet can examine and investigate an image in multiresolution at a different frequency band, because of the finite duration and a varying scale nature of basis functions of

wavelet, which decomposes the image into a set of detail and approximation coefficient

The analysis and synthesis implementation of discrete wavelet transform decrease time for computation satisfactorily and very simple to execute. It can examine and investigate an image in multiresolution at a different frequency band. It decomposes the image into a set of detail and approximation coefficient [13].
.
The forward equation for the computation of wavelet coefficient is given by

$$w_{m,n} = \langle f(t), \psi_{a,b} \rangle = a_0^{m/2} \int (f(t)\psi (a_0^m(t) - nb_0)dt \quad (2)$$

The synthesis equation to rebuild the image x (m,n) is given by

$$x(m,n) = \sum_m \sum_n w_{m,n}\psi_{a,b}(m,n) \quad (3)$$

Wavelet split an image into a series orthogonal images of translated and scaled form of mother wavelet, which is the basis function. In analogue implementation, both the translation and scaling operations are analogous to the low pass and a high pass filter, while its digital counterpart is a moving difference and moving average respectively [14].

Wavelet denoising can smooth the noise affected areas in a medical image, without affecting information content areas. In wavelet transformed noisy image LL band coefficients are relevant information of that entire image. Noisy components are separated and available in HH band coefficients [15]. Therefore, wavelet transform gives way easier to eliminate the noisy components present in the HH band, without altering other band coefficients. The selection of threshold value, used for filtering the noisy components is an important process, which requires the complete knowledge of the signal and an estimate of the thresholding process. The thresholding is a global and non-linear technique which take account of the nature of wavelet coefficients and the Standard Deviation (SD) of the noise. The value of threshold 'T' is calculated by using the equation with the wavelet coefficient 'N' and SD value of noise [16].

$$T = \sigma\sqrt{2\ log\ N} \quad (4)$$

## 3 Total Variation Minimization

A minimization technique 'Total Variation' was devised by Rudin, Osher, and Fatemi [17] and researcher designed image restoration technique by using TV based filtering to remove the noise with the excellent preservation of edges. The nonlinear nature of TV denoising efficiently restores piecewise-constant signals. It transforms the smoothly varying regions into piecewise constant regions. The basic idea of TV is to solve the fourth order partial differential equation, which measures the signal changes between signal values. The TV of an M-point signal y (k), $1 \leq k \leq M$, is defined mathematically as

$$TV(y) = \sum_{k=2}^{M} |y(k) - y(k-1)| \quad (5)$$

The TV of a variable 'y'is given as matrix TV(y) = $\|D_y\|_1$
Where $\|.\|_1$ is the $\rho 1$ norm and

$$D = \begin{bmatrix} -1 & 1 & & & \\ & -1 & 1 & & \\ & & \ddots & & \\ & & & -1 & 1 \end{bmatrix}$$

D is a (M-1) x M size matrix.
Usually, the medical image contains geometric descriptions such as highly connected pixels and objects, with smooth edges and borders. The variation of brightness considered as constant in the inside of the object and abrupt changes on the perimeter. We assume that the signal x is degraded by additive white Gaussian noise

$$y = x + nx, y, n \in R^N \quad (6)$$

TV denoising minimise the objective function and estimate the signal 'x'

$$J(x) = \|y - x\|_2^2 + \delta\|Ax\|_1 \quad (7)$$

This objective function can be minimized by the iterative clipping algorithm [18]

$$x^{(I+1)} = y - A^t z^{(i)} \quad (8)$$

$$z^{(I+1)} = clip\left(z^i + \frac{1}{\alpha}Ax^{(I+1)}, \frac{\delta}{2}\right) \quad (9)$$

$$for\ i \geq 0\ with\ z^{(0)} = 0\ and\ \alpha \geq maxeig(AA^t)$$

For the matrix D, the maximum Eigen value of D is less than four regardless of N, so far TV denoising we can set α = 4.

## 4. The Proposed method

### 4.1 Algorithm

The various steps of our proposed algorithm: are summarised below

1. Wavelet transform of the required level is performed on the noisy image, which decomposes the entire image pixels into four different level wavelet coefficients, LL, LH, HL and HH,

2. An exact value of threshold is selected for each level.
3. TV algorithm, as explained in section 2.2 is applied to the wavelet threshold coefficients
4. The inverse wavelet transform is performed on the transformed and thresholded coefficients to restore the original image.

Figure 1 shows the detailed block diagram of the proposed denoising method.

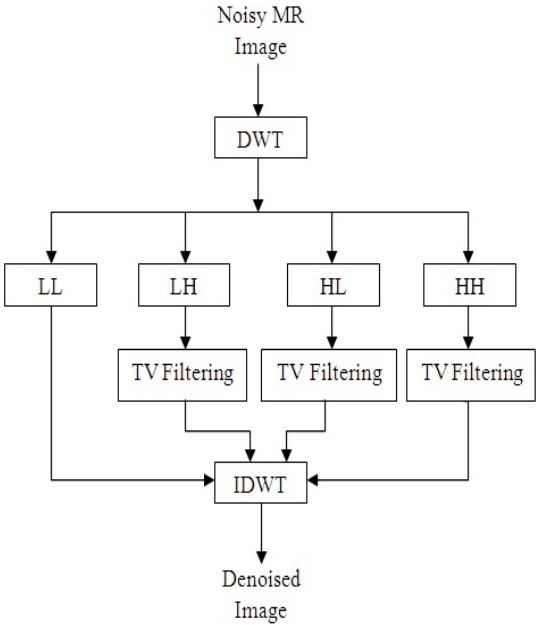



Figure 1. Flow chart of proposed method

## 4.2 Quality Assessment

In our method of denoising quality of the denoised image is assessed by two categories of evaluation criteria [19]. One set of metric measures entropy and variance reveals the image features and the second set of metric measures such as Peak Signal to Noise Ratio (PSNR) compares the denoised image with the original corrupted image [20].

The criteria entropy assesses the measure of the amount of information in an image. The estimation of entropy in a noisy image is constantly low. The higher estimate of entropy in denoised images demonstrates better denoising performance. The entropy is calculated as

$$H = -\sum_{i=0}^{L-1}(P_i x \log_2 P_i) \quad (10)$$

Where $p_i$ is the probability distribution of each grey level, L is the total of grey levels. The maximum value of entropy in a grey-scale image is 1.

SD is an estimate of the brightness probability distribution, which reveals the deviation of image, grey contrast to the mean. The estimation of SD in a noisy image is constantly high. The lower estimate of SD in denoised images demonstrates better denoising performance. The SD is calculated as

$$\sigma^2 = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(X(i,j) - \mu)^2 \quad (11)$$

Where M and N is the size of the image and, μ is the mean of the image, which is defined as

$$\sigma^2 = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(X(i,j) - \mu)^2 \quad (12)$$

The RMSE gives the difference in intensity values between two images. The lower the value of RMSE indicates a better performance of denoising. RMSE is calculated for M X N images using the formula [21]

$$RMSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(R(i,j) - X(i,j)^2 \quad (13)$$

PSNR is also another spatial content measure of an image based on RMSE and its maximum grey value 'fmax'. The higher value indicates the better fusion performance. It is calculated using the formula

$$PSNR = 10\ \log(\frac{255^2}{RMSE^2}) \quad (14)$$

## 5. Experimental Result & Discussion

We tested our proposed method of denoising on 20 numbers of brain MRI images corrupted with Random and Gaussian noises using MATLAB, and we tabulated for four images. Various noise factors are used in denoising of random noise, and different SD values are taken into account while denoising Gaussian corrupted images. Here we tabulated the results of four MR images with a noise factor of 30 are used for random noise, and standard deviation of 20 is used for Gaussian noise. We applied the Wavelet based TV method of denoising to obtain better image denoising. For comparing our results with the conventional method, we performed the hard threshold and wavelet transform by Debauchees wavelet with four levels of decomposition.

Figure 2 shows that PSNR, Mean, SD and Entropy values of denoised images of MR images, using Wavelet and TV based thresholding wavelet denoising for MR images corrupted by random noise. It is evident that from this figure, our method of denoising gives a higher value of PSNR and Entropy, than the wavelet method of denoising. And also our technique of denoising provides the lower amount of Mean and SD, than the wavelet method of denoising, which is also the excellent measure of the performance of our denoising technique.

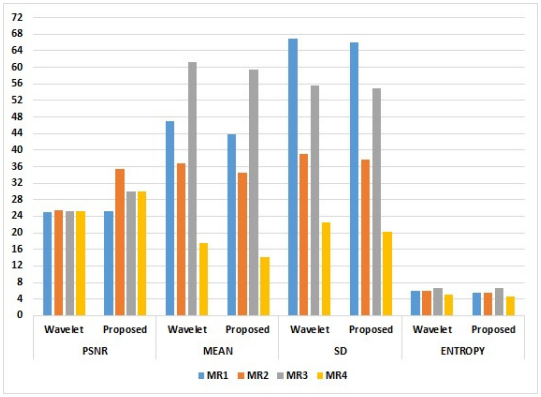



Figure 2. PSNR, Mean, SD, and Entropy values for denoised images corrupted by random noise

Figure 3 shows that PSNR, Mean, SD and Entropy values of denoised images of MR images, using Wavelet and TV based thresholding wavelet denoising for MR images corrupted by Gaussian noise. It is evident that from this figure, our method of denoising gives the higher value of PSNR and Entropy, than the wavelet method of denoising. And also our technique of denoising provides the lower amount of Mean and SD, than the wavelet method of denoising, which is also the excellent measure of the performance of our TV based wavelet denoising technique.

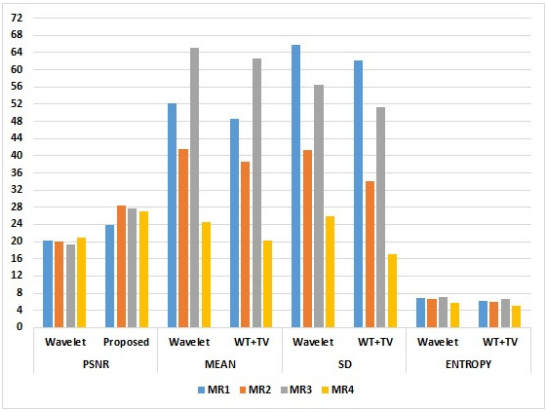


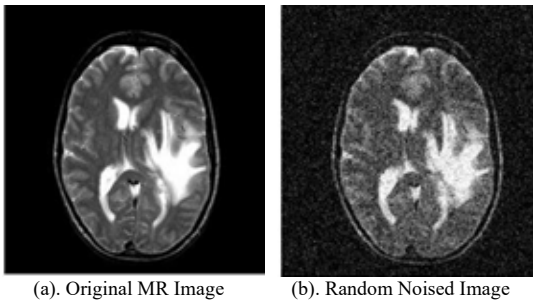

Figure 3. PSNR, Mean, SD, and Entropy values for denoised images corrupted by Gaussian noise

Table-1 shows the PSNR, Mean, SD and Entropy values of the denoised MR images. It revealed that TV based wavelet denoising is an excellent technique regarding PSNR, Mean, SD and Entropy value, compared to the wavelet denoising method

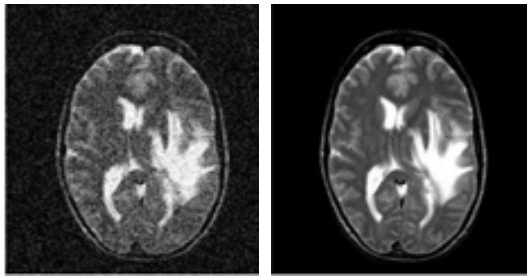
Table-1 PSNR, MEAN, SD, ENTROPY values for Denoised Images

| Image | Noise | PSNR | | MEAN | | SD | | ENTROPY | |
|---|---|---|---|---|---|---|---|---|---|
| | | Wavelet | WT+TV | Wavelet | WT+TV | Wavelet | WT+TV | Wavelet | WT+TV |
| MR1 | Random | 25.0520 | 25.1289 | 46.9470 | 43.8244 | 67.0402 | 65.9456 | 6.0314 | 5.5668 |
| | Gaussian | 20.3223 | 23.8915 | 52.2344 | 48.6808 | 65.7363 | 62.2269 | 6.7797 | 6.0870 |
| MR2 | Random | 25.4674 | 35.5114 | 36.7038 | 34.5424 | 38.9956 | 37.5916 | 5.9996 | 5.5600 |
| | Gaussian | 19.9141 | 28.4172 | 41.6131 | 38.6489 | 41.3076 | 34.0303 | 6.6364 | 5.8995 |
| MR3 | Random | 25.3417 | 29.9529 | 61.2918 | 59.4792 | 55.6642 | 54.8169 | 6.7195 | 6.6070 |
| | Gaussian | 19.4233 | 27.7202 | 65.2109 | 62.6158 | 56.5512 | 51.2061 | 7.1981 | 6.6578 |
| MR4 | Random | 25.1905 | 29.8971 | 17.4765 | 14.1558 | 22.4093 | 20.2599 | 4.9553 | 4.6050 |
| | Gaussian | 20.8183 | 26.9546 | 24.6098 | 20.1913 | 25.9798 | 17.0587 | 5.7854 | 4.9620 |

The original and random noise degraded MR images are shown figure 4(a) and (b). The denoised images using wavelet and our proposed algorithm are shown in figure 4(c) and (d). For random noised degraded images, our proposed denoising algorithm yields denoised image with improved PSNR 32.5154 dB, whereas the PSNR 24.46dB of wavelet method.



(a). Original MR Image (b). Random Noised Image

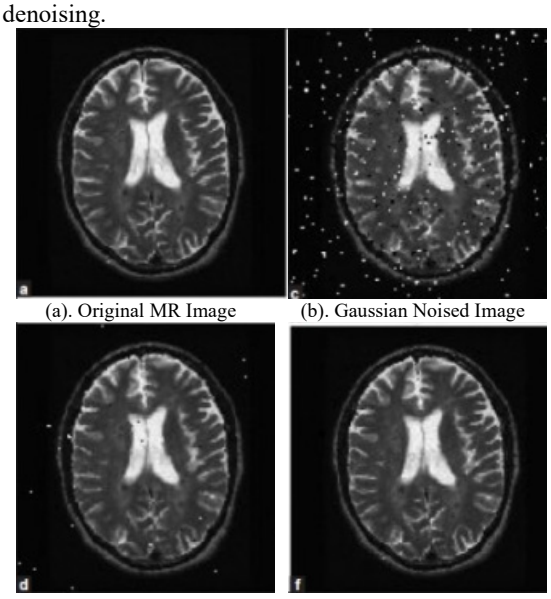


(c ). Wavelet Denoised Image (d) Proposed Denoised Image

Figure 4. Denoising of MR image corrupted by Random Noise (MR1)

The original and Gaussian noise degraded MR images are shown figure 5(a) and (b). The denoised images using wavelet and our proposed algorithm are shown in figure 5(c) and (d). For Gaussian noised degraded images, our proposed denoising algorithm yields denoised image with improved PSNR 28.41 dB, whereas the PSNR 19.91dB of wavelet method.

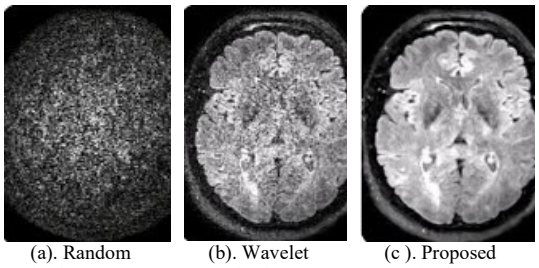
Figure 6, 7, 8 show the result of our proposed denoising method and the wavelet denoising method of various MR images. We took the different human organ MR images which are both corrupted by random and Gaussian noise, for the study of proposed denoising method. In all these figures (a) represents the noised image, (b) represents Wavelet denoised image and (c) represents the resultant denoised of our proposed technique. It is apparent that our denoising method gives sharper images than the wavelet denoising.



(a). Original MR Image (b). Gaussian Noised Image

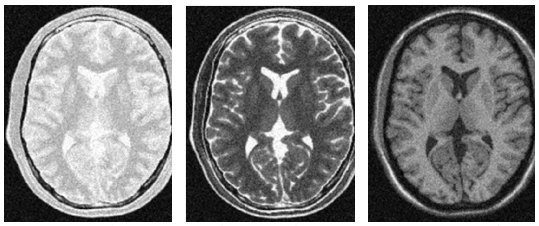
(c ). Wavelet Denoised Image (d) Proposed Denoised Image

Figure 5. Denoising of MR image corrupted by Gaussian noise (MR1)



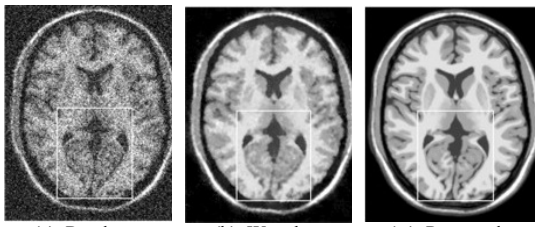
(a). Random Noised MR Image (b). Wavelet Denoised Image (c ). Proposed Denoised Image

Figure 6. Denoising of MR image corrupted by Random Noise (MR2)



(a). Gaussian Noised MR Image (b). Wavelet Denoised Image (c ). Proposed Denoised Image

Figure 7. Denoising of MR image corrupted by Gaussian Noise (MR3)



(a). Random Noised MR Image (b). Wavelet Denoised Image (c ). Proposed Denoised Image

Figure 8. Denoising of MR image corrupted by Random Noise (MR4)

## 6. Conclusion

Our experiments compare and contrast wavelet denoising and TV based thresholding wavelet denoising methods. The TV based thresholding wavelet denoising method is proposed for denoising MR images. Our research article suggests an improved algorithm which overcome the deficiencies of the conventional denoising methods based on wavelet transform. We used MR images corrupted by random noise with several noise factors and Gaussian noise with different SD values to test our algorithm. We applied our algorithm TV based thresholding wavelet denoising and the conventional wavelet-based thresholding. It is evident from the result that the wavelet threshold denoising method, affect the edge and detailed information, in the restored image. But the TV based thresholding wavelet denoising method retained detail information with edge preservation in an excellent way than wavelet thresholding. The TV-based thresholding wavelet denoising technique attained a superior level of restoration, which serves the precise diagnosing ability to the MR radiologist. Our result proved that TV-based thresholding wavelet denoising method is a small breakthrough in the traditional denoising method for denoising MR images, corrupted by random and Gaussian noises.

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